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Identification of the Parameters of a Photovoltaic Cell Using an Improved Genetic Algorithm (GA) Technique and Particular Swarm Optimization (PSO)

Abstract. *The modeling of a photovoltaic cell predicts the behavior of the cell in various environmental contexts of the real world, the identification of the parameters of the photovoltaic cell is essential to simulate the behavior and to optimize the different characteristics of a photovoltaic cell (better energy management and good operating reliability). In this work, two intelligent algorithms were used and compared for the identification of the parameters of a photovoltaic cell. The proposed approach combines the simplicity of the equations of the explicit method with that of two meta-heuristic methods, namely the genetic algorithm (GA) and the particle swarm optimization algorithm (PSO). These techniques used for the identification of the parameters of the unknown model namely the photos run (I_{ph}), the current of saturation (I_s), the resistance series (R_s), and the factor of ideality (A) is last to govern the relation current - voltage of a solar cell. The objective is to create an objective function that aims to solve an optimization problem (find the optimal solution in terms of parameters), The panels studied in this work is the RTC France, and the characteristic curves of the panel are obtained using only the information provided by the manufacturer's datasheet, thus avoiding the need to carry out experimental data. The performances and the precision of the proposed method are evaluated by applying the model to a diode with four unknown parameters, the combination of the explicit equations with Meta-heuristic techniques allows to obtain an excellent performance of optimization and a high precision of estimation of the results, The choice of the parameters PSO and GA is very important for a faster convergence of the algorithm.*

Streszczenie. *Modelowanie ogniwa fotowoltaicznego przewiduje zachowanie ogniwa w różnych kontekstach środowiskowych świata rzeczywistego, identyfikacja parametrów ogniwa fotowoltaicznego jest niezbędna do symulacji zachowania i optymalizacji różnych charakterystyk ogniwa fotowoltaicznego (lepsze zarządzanie energią i dobra niezawodność działania). W tej pracy wykorzystano i porównano dwa inteligentne algorytmy do identyfikacji parametrów ogniwa fotowoltaicznego. Proponowane podejście łączy prostotę równań metody jawnej z prostotą dwóch metod metaheurystycznych, mianowicie algorytmu genetycznego (GA) i algorytmu optymalizacji roju cząstek (PSO). Techniki te służą do identyfikacji parametrów nieznanego modelu, mianowicie przebiegu zdjęć (Iph), prądu nasycenia (Is), szeregu rezystancji (Rs) i współczynnika idealności (A), aby ostatecznie określić relację prąd - napięcie ogniwa słonecznego. Celem jest stworzenie funkcji celu, która ma na celu rozwiązanie problemu optymalizacji (znalezienie optymalnego rozwiązania pod względem parametrów). Panele badane w tej pracy to RTC France, a krzywe charakterystyczne panelu uzyskano, korzystając wyłącznie z informacji dostarczonych przez kartę danych producenta, unikając w ten sposób konieczności przeprowadzania danych eksperymentalnych. Wydajność i precyzja proponowanej metody są oceniane poprzez zastosowanie modelu do diody o czterech nieznanych parametrach. Połączenie równań jawnych z technikami metaheurystycznymi pozwala uzyskać doskonałą wydajność optymalizacji i wysoką precyzję szacowania wyników. Wybór parametrów PSO i GA ma bardzo duże znaczenie dla szybszej zbieżności algorytmu. (Identyfikacja parametrów ogniwa fotowoltaicznego przy użyciu ulepszonej techniki algorytmu genetycznego (GA) i optymalizacji roju (PSO)).* ***(Identyfikacja parametrów ogniwa fotowoltaicznego przy użyciu techniki ulepszonego algorytmu genetycznego (GA) i optymalizacji roju szczególnego (PSO))***

Keywords: Identification, Artificial Intelligence, Photovoltaic, Genetic Algorithm, Optimization, Particular Swarm
Słowa kluczowe: Identifikácia, Umelá Inteligencia, Fotovoltaika, Genetický Algoritmus, Optimalizácia, algorytm rojowy

Introduction

Artificial intelligence (AI) and renewable energy are two areas that can complement each other and contribute to the transition to a more sustainable future. Since 2020, the development of renewable energies is progressing around the world. In particular in the field of solar and wind energy. Many countries are increasing their investments in renewable energies. Energy costs continue to fall as technology advances and plant efficiency increases [7], [20].

Solar energy is generated by directly converting sunlight into electricity using photovoltaic panels [1], [16].

The photovoltaic industry has grown exponentially as installed capacity has increased rapidly in many countries around the world and the manufacturing cost of photovoltaic panels has decreased [2].

This makes it more competitive compared to conventional energy sources.

A photovoltaic system produces energy that depends on environmental conditions such as temperature, solar radiation and the orientation of the photovoltaic panel [17], [26]. The characteristics of the photovoltaic panel under standard conditions (STC) are provided by the manufacturers [18], The behavior of a PV module is usually described by its characteristics current - voltage, I-V, power-voltage P-V, the latter depend on five parameters, Is, Iph, Rs, Rsh, A The precision and the number of parameters used Different from each model [19], [27].

Artificial intelligence can be used to identify the parameters of solar cells. The combination of solar energy and artificial intelligence can optimize solar energy production, performance and management [3], contributing to more efficient use of resources and lower costs.

The aim of this article is to present a simple process, based on simplified explicit equations combined with meta-heuristic methods, which will allow us to estimate the unknown parameters of our panel. The exploitation of the results will be made by a numerical method implemented in the MATLAB environment.

Thus the results obtained allow a comparison between the two meta-heuristic methods used for the experimental validation of our approach.

Methods of Identification of PV Cells

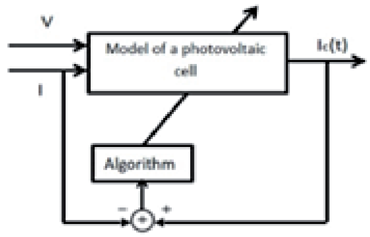

Fig. 1. Identification principle

Several techniques have been developed to extract solar cell parameters. They can be classified according to the technology used [8].

1. Experimental characteristic.
2. Data provided by the manufacturer.

Our classification is based on identification methods. We can distinguish them in three points:

Analytical methods

The latter uses the I-V characteristics specified by the manufacturer under standard operating conditions, the unknowns are represented by equations in mathematical form and the effectiveness of this technique depends on the accuracy of the measurements.

Numerical methods

Numerical techniques are methods based on iterative algorithms such as: Newton Raphson, least squares, etc.

Heuristic/meta-heuristic methods

In recent years, optimization methods using artificial intelligence techniques have been widely adopted and developed by researchers because of their ability to solve complex and nonlinear problems.

Optimization heuristic

It is Simple, fast and adaptable to a specific problem. His ability to optimize a problem with minimal information is compounded by the fact that he cannot guarantee that the best solution he finds is optimal. From an operations research perspective, this flaw is not always a problem, especially when only an approximation of the optimal solution is desired [4].

Meta-heuristics

Some heuristic algorithms can be adapted to different problems without much modification of the algorithm, these are meta-heuristic algorithms. Most heuristics and meta-heuristics use stochastic processes as a way to collect information and deal with problems like combinatorial explosion. Outside of this probabilistic basis [5], encounter heuristics are typically iterative, i.e. apply the same search pattern multiple times during optimization and simply do not use information from the objective function gradient [4].

They are particularly interested in the ability to avoid local optima by accepting the degradation of the objective function with evolution or by using groups of points as a search method [1]. (This distinguishes it from local descent heuristics).

They are often inspired by analogies with reality (physics, biology, ethology, etc.) and were typically originally developed for discrete problems, but adapted to continuous problems and can be applied to many different problems. There are several such methods in the literature, including: Particular Swarm Optimization (PSO), Genetic Algorithm (GA), Bee Swarm Optimization (BSO) and Ant Colony Optimization (ACO).

Mathematical model

Ideal model

Several models have been proposed in the literature. The objective is to simulate the behaviour of solar cells under various conditions [21]. Fig. 2 shows the equivalent circuit of the ideal photovoltaic cell, it includes a constant current source, in parallel with a diode.

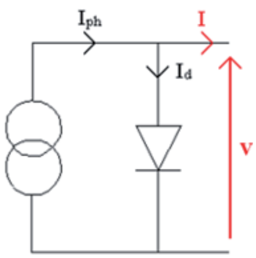

Fig. 2. Equivalent circuit

Mathematically fundamental equations of an ideal solar cell is represented in Equation (1)

$$I = I_{ph} - I_o \left(\exp\left(\frac{V + R_s I}{V_t a} \right) - 1 \right) \quad (1)$$

$$I_d = I_o \left(\exp\left(\frac{q(V + R_s I)}{aKT} \right) - 1 \right) \quad (2)$$

Where I_{ph} is the photo-current, I_d is the diode reverse saturation current, I and V are the values obtained from current and voltage, V_t is the thermic voltage, K is Boltzmann constant $1,38 \cdot 10^{-23} J/K)$, N_s is the cell connected in series (provide higher output voltages), N_p is the cell connected in parallel (increase the current), T is the temperature (K), q is the electron charge $1,6 \cdot 10^{-19} C$ and E_g is the bandgap energy of the semiconductor [10].

Simple diode

A single diode equivalent circuit of a Solar cell is shown in Fig. 3.

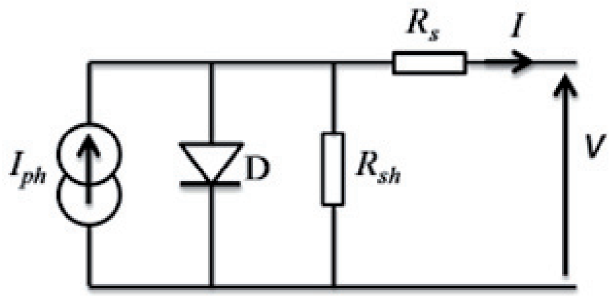

Fig. 3. Simple equivalent circuit diagram of a solar cell [6]

The circuit in Fig. 3 consists of a constant current source in parallel with a diode. This model takes into account the internal series resistance of the module and the losses due to the contacts and connections between the cell and the module. The parallel resistance of the module, on the other hand, models the losses due to the leakage current through the junctions of the cells. This model offers a good compromise between approximation accuracy and simplicity [10].

The latter is called a single diode model, widely used to represent the behavior of solar cells. The output current is given as follows:

$$I = I_{ph} - I_d - I_{sh} \quad (3)$$

$$I_d = I_o \left(\exp\left(\frac{q(V + R_s I)}{aKT} - 1 \right) \right) \quad (4)$$

$$I_{sh} = \frac{V + R_s I}{R_{sh}} \quad (5)$$

Where I_{ph} and I_o are the photovoltaic current and the saturation current, I_{sh} replaces the current of the shunt resistor.

$$I = I_{ph} - I_o \left(\exp\left(\frac{V + R_s I}{V_t a} - 1 \right) - \frac{V + R_s I}{R_{sh}} \right) \quad (6)$$

(7) $$V_t = \frac{KT}{q}$$

All photovoltaic system data sheets basically have the following information:

no-load voltage $V_{oc,n}$, short-circuit current $I_{sc,n}$, maximum power point voltage V_{mp}, maximum power point current I_{mp}, open circuit voltage/temperature coefficient K_V, short circuit current/temperature coefficient K_I and maximum experimental peak power P_{max},. This information is always provided with reference to: Rated or standard test conditions (STC) of temperature and sunlight exposure. Some manufacturers provide I-V curves compatible with various irradiation conditions and temperature conditions. These curves facilitate the following adjustments and validations.

The "I-V" characteristics of the photovoltaic device depend on the device's internal characteristics (R_s, R_{sh}) and external influences such as solar radiation levels and temperature. Cells connected in parallel increase current, while cells connected in series provide higher output voltage.

The luminous flux of the solar cell depends linearly by the solar radiation and the temperature According to the following equations [22].

(8) $$I_{ph} = (I_{ph,n} + K_i\Delta_T)\frac{G}{G_n}$$

(9) $$\Delta_T = T - T_n$$

Where $I_{ph,n}$ is the light-generated current at the nominal condition.

The diode saturation current I_o and its temperature dependence can be expressed as:

(10) $$I_o = I_{o,n}\left(\frac{T_n}{T}\right)^3 \exp\left[\frac{qE_g}{aK}\left(\frac{1}{T_n} - frac1T\right)\right]$$

And $I_{o,n}$ is the nominal saturation current:

(11) $$I_{o,n} = \frac{I_{sc,n}}{\exp\left(\frac{V_{oc,n}}{aV_{t,n}} - 1\right)}$$

The saturation current I_o of PV cells depend on the saturation current density of the semiconductor (I_o, usually given in $[A/cm^2]$). The current density I_o depends on the intrinsic value characteristics of the PV cell.

Equation (10) is replaced by the equation below with a view to improving

(12) $$I_o = \frac{I_{sc,n} + K_i\Delta_T}{\exp\left(\frac{V_{oc,n}+K_i\Delta_T}{aV_t}\right) - 1}$$

The purpose of this modification is to adapt the open circuit voltage of the model to the experimental data over a very wide temperature range. Fig. 12 is derived from Equation (11) by including the current/voltage coefficients KI, KV in the equation.

The saturation current I_o strongly depends on the temperature. This equation simplifies the model and eliminates adjacent model errors [11].

Identification Parameters of The PV Cell Using Meta-heuristic Methods

Genetic algorithms

Genetic algorithms were introduced by Holland in the 1975 [12]. Their field of application is very wide. Besides economy, it is also used for other system optimizations.

A genetic algorithm (GA) is a stochastic optimization algorithm. This method of optimization draws on natural selection processes and genetics to solve complex problems. It can also be used to determine photovoltaic parameters [13].

The identification of the photovoltaic parameters consists in finding the optimal values for different parameters that describe the behavior of the photovoltaic module, such as: the saturation current, the photo-current, the ideality factor, the series resistance, the parallel resistance, etc.

Their evolutionary process is random and controlled by three mechanisms: Selection, crossing, mutation.

GA maintains a set of candidate solutions called the population and modifies them iteratively using three mechanisms, at each iteration we start with an initial randomly selected population of potential solutions (chromosomes). Each performance (fitness) will be evaluated. Based on these results, we create new populations of potential solutions using simple evolution operators: Selection, crossing and mutation. We repeat this cycle until we find a satisfactory solution [12].

This procedure is summarized in the flowchart in Fig. 4.

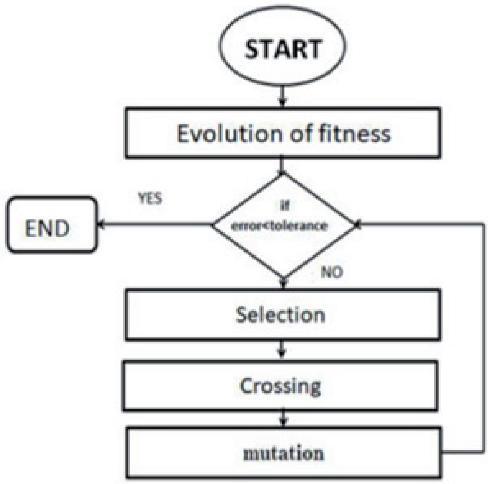

Fig. 4. GA flowchart

Particle Swarm Optimization

The Particle Swarm Optimization (PSO) algorithm is an evolving 'meta-heuristic' method for determining the optimal parameters of a photovoltaic system. It was originally proposed by Kennedy and Eberhart as a simulation of the social behavior of social organisms such as flocks of birds and schools of fish in research spaces. It can also be used to determine photovoltaic parameters [21].

PSO differs from other methods of evolutionary computation in that members of the population called "particles" are dispersed in the problem space. Therefore, the behavior of a particle swarm must be described in terms of particles. Each particle has the following characteristics:

- The position, that's to say its coordinates in the definition set.
- The speed at which the particles can move. This way, each particle will change position during the iteration. It evolves based on its best neighbors, its best location,

and its previous location.

It can quickly explore the search space and find quality solutions. However, it can also be sensitive to local minima. Therefore, it is important to carefully choose the parameters of the algorithm [23]. By applying this method to optimization problems, she takes advantage of the physical movements of individuals within a herd and organizes them in a random and balanced way to improve and adapt global and local search capabilities. Particles are the final movement in the search space. Each of the particles is considered as a solution of the problem and has a position $X_{i,j}$ and a speed $V_{i,j}$ In addition; each particle has a memory of its best visited position $P_{i,best}$ and also of that of its neighborhood $P_{i,Gbest}$.

PSO uses the velocity vector information and the local and global best quality positions to update the current values of the solar cell parameters for each particle in the swarm. Thus, the value of the optimization function at each position of each swarm particle is calculated.

This updates the velocity vector associated with each particle based on the value of the solar cell and each particle's function [14].

Mathematically, the estimate of the « i » solar cell parameter for the « j » particle in the swarm at iteration k+1 is updated as

$$X_{i.j}^{k+1} = X_{i.j}^{k} + V_{i.j}^{k+1} \tag{13}$$

Where $V_{i.j}^{k+1}$ is the updated velocity vector.

The velocity vector associated with each solar cell parameter is calculated as, the « k+1 » iteration is updated

$$V_{i.j}^{k+1} = wV_{i.j}^{k} + C_1 r_{i.j}^{k}(P_{i.best}^{k} - X_{i.j}^{k}) + C_2 r_{2.j}^{k}(P_{i.Gbest}^{k} - X_{i.j}^{k}) \tag{14}$$

Where $V_{i.j}^{k}$ is the velocity vector, $X_{i.j}^{k}$ is the swarm particle at iteration k, $P_{i.best}^{k}$ is the best recorded individual value, $P_{i.Gbest}^{k}$ is the best recorded overall value, $r_{i.j}^{k}$, $r_{2.j}^{k}$ represent a random number varying between [0, 1] and w, C_1 and C_2 are respectively the inertial weight, the cognitive parameter and the social parameter [24].

The steps of the algorithm are illustrated in Fig. 5.

Particle swarm optimization is one of the most widely used techniques due to its easy implementation and inexpensive computation, simplicity of coding and consistent performance.

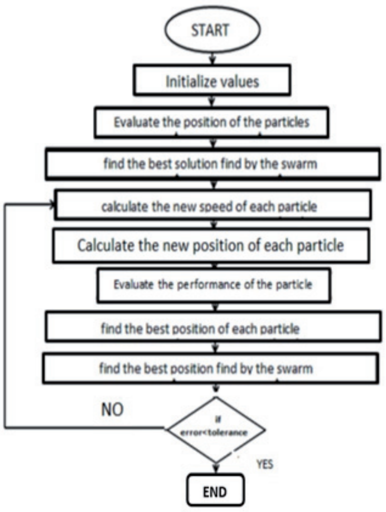

Fig. 5. PSO algorithm

Identification of PV Cell Parameters Using Meta-heuristic Methods Combined With Explicit Equations

The method proposed in this article combines the algorithms of the particle swarm (PSO), a common way to calculate the unknown parameters (I_{ph}, I_s, R_s, A), by using explicit equations which are also used to calculate the parameters of the model of photovoltaic modules with diodes in a direct way (mathematical equations). That is to say without the need to resort to iterative methods, the second one combines its last with the genetic algorithm (GA).

The three methods require knowing the values of the current (I_{mp}) and the voltage (V_{mp}) as well as the short-circuit current (I_{sc}) and the open-circuit voltage (V_{oc}).

In our work we studied the model of the France RTC cell under standard conditions as represented in Table. 1 with a constant illumination of $1000w/m^2$:

Table 1. Cell data sheet of RTC FRANCE

V_{mp}	I_{mp}	V_{oc}	I_{cc}	T	N_s
0.4507	0.6894	0.5728	0.7603	33	1

Objective function

To extract various solar cell model parameters from I-V data using optimization techniques, we need to define performance criteria or objective functions. To define the objective function [25] rewrite the current-voltage relationship (i-v) given in Equation (1) as:

$$f(I, V, X) = 0 \tag{15}$$

Where $X = [I_{ph}, I_o, R_s, R_{sh}, A]$ is the decision vector which consists of the parameters to be extracted. For each parameter, it is bounded in the search space [19].

The objective function f in Equation (20) must be minimized. The smaller the objective function, the better the solutions obtained. It is calculated using explicit equations for four-parameter identification:

We suppose that: $R_{sh} = \infty$

- The expression of the photocurrent I_{ph} is given by:

$$I_{ph} = (I_{ph,n} + K_i \Delta_T)\frac{G}{G_n} \tag{16}$$

- The expression of the reverse saturation current of the diode I_o is written:

$$I_o = I_{o,n}\left(\frac{T_n}{T}\right)^3 \exp\left[\frac{qE_g}{aK}\left(\frac{1}{T_n} - \frac{1}{T}\right)\right] \tag{17}$$

Expression of resistance:

$$R_s = \frac{\frac{N_s AKT}{q}\ln\left(1 - \frac{I_m}{I_{cc}}\right) + V_{co} - V_m}{I_m} \tag{18}$$

The expression of the ideality factor:

$$A = \frac{q(2V_m - V_{co})}{N_s KT\left[\frac{I_{cc}}{I_{cc} - I_m} + \ln\left(1 - \frac{I_m}{I_{cc}}\right)\right]} \tag{19}$$

The latter are used to find an approximate estimate of the unknown parameters, which leads to restrict the search space appropriately, thus allowing a faster convergence towards the optimal solution [11].

The value of " f " is calculated for each pair of measurement data. In this article, square root means root mean square error (RMSE), is chosen as the criterion to quantify the difference between the model results and the measured data [15]. RMSE is defined by the following formula:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} f_i(I_i, V_i, X)^2} \tag{20}$$

Where N is the number of data points.

Results

To compare the efficiency of the two algorithms to improve, we have chosen to study the RTC France panel Table. 2. The parameters of the algorithms are represented in the following table:

Table 2. Parameters of two algorithms PSO and GA

PSOX	GAX
Population size:100	Population size:1000
$C_1 : 1.5$	Selection: uniform stochastic
$C_2 : 2$	Crossover: random
W: 0.9	Mutation: Gaussian
Number of iteration:5000	Number of iterations :5000

The PV module parameters were estimated under standard temperature and irradiance conditions using the SDM diode model of the RTC France photovoltaic module. The optimal values for the four parameters (I_{ph}, I_o, R_s, A) are represented in Table. 3.

Table 3. Simulation result

	PSO	PSOX	GA	GAX
I_{ph}	0,7565	0,7586	0,760324	0,75898
I_s	2,66E-07	8,88E-07	2,47E-06	1,09E-06
R_s	0,03811	0,03256	0,026716	0,03114
A	1,48	1,58985	1,7647	1,61449
RMSE	0,0033	0,00245	0,003943	0,001047

To test the two algorithms, we chose a population of 1000 individuals for GA, the results obtained after 100 iterations are represented in the following figure, for the PSO-explicit method we chose a population of 50 (PSOX) with 5000 iterations, the first and the second column show the values for the algorithm of the particular swarm (PSO) and the algorithm of the particular swarm combined with explicit equations (PSOX), the third and fourth column represents the genetic algorithm and the genetic algorithm combined with the explicit equations.

The characteristic curves current-voltage "I-V", power-voltage "P-V" can be easily reconstructed as shown in Fig. 6.

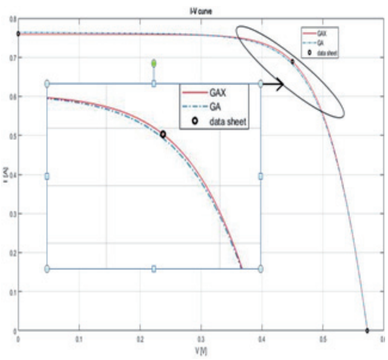

Fig. 6. GAX and GA comparison I-V

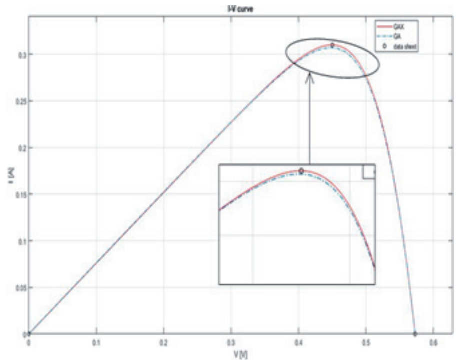

Fig. 7. GAX and GA comparison P-V

The characteristics of Fig. 6 and Fig. 7 current-voltage and power-voltage obtained show that the simulation results and the manufacturer's data are very close, in particular the genetic algorithm method combined with explicit equations in terms of value and faster convergence.

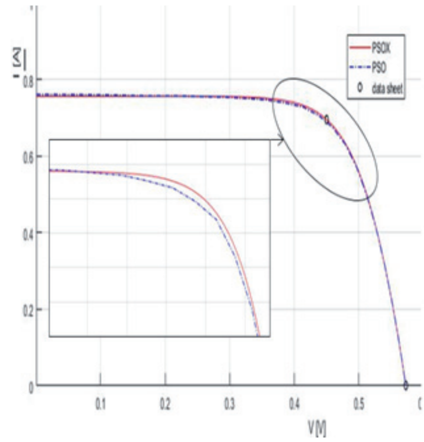

Fig. 8. PSOX and PSO comparison I-V

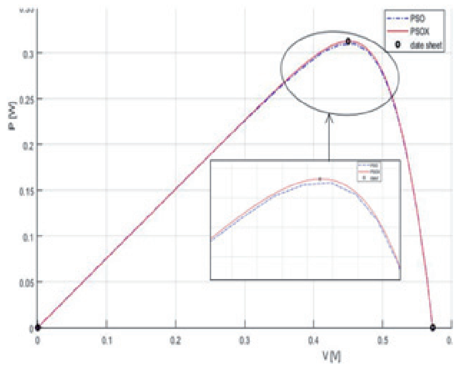

Fig. 9. PSOX and PSO comparison P-V

In the following figure, which represents the characteristic curves of the I-V and P-V of the simple and explicit PSO algorithm, we notice an improvement in the PSOX curve thanks to the use of explicit equations that reduces the calculation load, and total control over the modelling.

Fig. 10 and Fig. 11 show the best value of the objective function during the iteration. As can be seen, the convergence speed of the proposed algorithm is fast. Indeed, in the case of genetic algorithms, we use explicit equations to evaluate the performance of each chromosome with an objective function (direct calculation of the values of the objective function). In our research, we found that the choice of parameters for both algorithms is very important for convergence.

Using explicit equations in either method implies that the objective function to be optimized is formulated in explicit

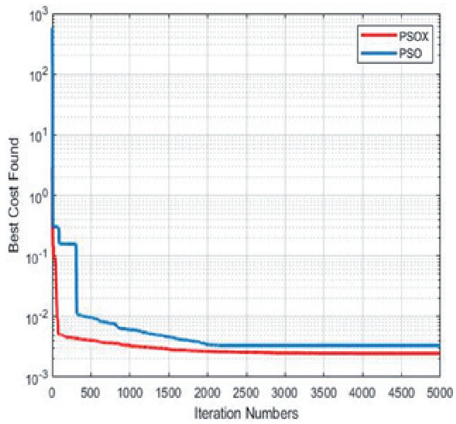

Fig. 10. PSOX and PSO convergence comparison

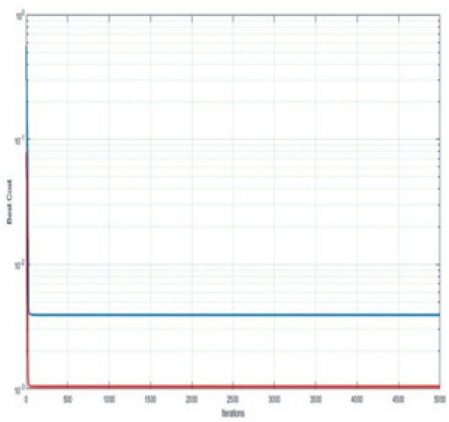

Fig. 11. GAX and GA convergence comparison

mathematical form. This means that the objective function can be determined directly from the solution parameters without the need for complex evaluations.

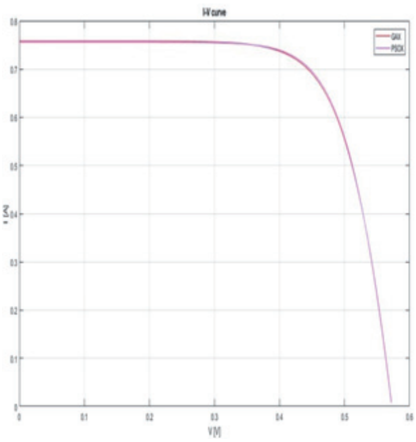

Fig. 12. Comparison between the I-V curves of the two methods

We notice slight differences between the two algorithms in the current-voltage and power-voltage curves (Fig. 13), and on the convergence side, we see that the genetic method converges very quickly with respect to the swarm.

Discussion

In this paper, we propose a new technology for extracting photovoltaic cell parameters based on particle swarm optimization and a genetic algorithm combined with explicit equations.

Consider a four-parameter model. The data used in the

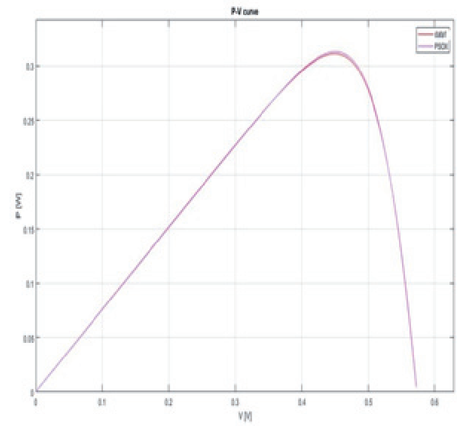

Fig. 13. Comparison between the P-V curves of the two methods

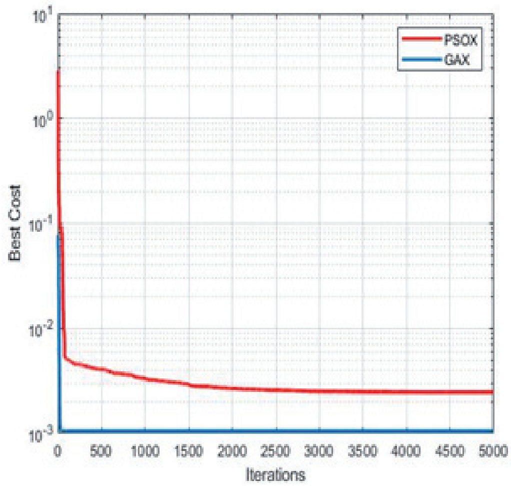

Fig. 14. Comparison between PSOX and GAX for convergence

simulations of our work correspond to commercial silicon solar cells (R.T.C France) at 33 C. Note that since the metaheuristic optimization algorithms are probabilistic in nature, in all the following simulations, the algorithm considered is run multiple times and the best result is presented in each case.

Genetic algorithm optimization is used for complex problems and a large search space, while particular swarm optimization is used as an optimization tool to increase the probability of reaching minimum global solutions in a short time. Time with very good precision based on the minimization of the squared error between experimental and theoretical characteristics.

The simulation results show that the accuracy of the heuristic approach is effective for modeling in the case of solar modules, comparing the results of the combined algorithm of PSO and GA; we can see that the minimum RMSE value provided by the GA is lower than that given by the PSO. The RMSE value obtained by the GA is 0.001047, which is lower than that 0.00245 given by the PSO.

Adding explicit equations allows us to quickly evaluate the performance of candidate solutions and gives us full control over our modeling. This allows us to direct the algorithm towards areas of the search space that are more promising in terms of convergence and acceleration. However, this requires a thorough understanding of the problem.

The performance of PSO and AG strongly depends on the configuration of each parameter such as population size, PSO rate factor, mutation and crossover rate of AG. Proper settings are essential for best results.

The choice between PSO and GA depends on the specific optimization problem we want to solve. For problems where rapid exploration of the search space is essential, PSO is often preferred, while GA is better suited to problems requiring robust, less parameter-sensitive search and deeper spatial exploration. It's usually a good idea to try both methods to determine which one suits your use case best.

Conclusions

In this work, we studied a simple and effective method to determine the parameters of RTC FRANCE solar panels using a single diode model. Heuristic and meta-heuristic methods are used to identify the parameters of photovoltaic modules.

The identification of photovoltaic parameters plays an important role in performance evaluation, product comparison, monitoring and maintenance of photovoltaic systems.

The methods proposed in this article. Particular swarm optimization and genetic algorithm optimization are two common approaches to solving optimization problems. Both methods are based on meta-heuristics inspired by natural phenomena.

Using an algorithm with explicit equations gives the following result:

A faster and more efficient optimization of the photovoltaic parameters facilitates the search for optimal solutions while allowing a better understanding and interpretation of the results obtained.

The combination of the genetic approach with explicit equations facilitates the search for optimal solutions and faster convergence.

The two evolutionary optimization approaches differ in their search mechanism, overall behaviour, and communication between solutions.

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REFERENCES

[1] SIARRY P. :Application des métaheuristiques d'optimisation en électronique, ITechniques de l'Ingénieur, traité Recherche et Innovation, RE (8), 2002.
[2] TERKI N., AZOUI B., et CHENNI R.: Thèse Zaghba Layachi, Biskra, algeria, 2017.
[3] BAFLAH A et BENABDELHAFID Y.: Acquisition des données en temps réel du panneau solaire. Thèse de doctorat. UNIVERSITY OF KASDI MERBAH OUARGLA,algeria, 2022.
[4] DRÉO J.: Adaptation de la métaheuristique des colonies de fourmis pour l'optimisation difficile en variables continues. Application en génie biologique et médical. 2003. Thèse de doctorat. Université Paris XII Val de Marne.
[5] BENYAMINA A.: Application des algorithmes de colonies de fourmis pour l'optimisation et la classification des images. 2013. Thèse de doctorat. USTO (MB).
[6] GUISSER M.:Stratégies de Commande pour l'Optimisation des Systèmes Photovoltaïques Autonomes et Connectés au Réseau. 2015. L'HABILITATION UNIVERSITAIRE, casablanca, marrakhech
[7] WANG R.: Parameter identification of photovoltaic cell model based on enhanced particle swarm optimization. Sustainability, 2021, vol. 13, no 2, p. 840.
[8] KHEZZAR R., ZEREG M., et KHEZZAR A. : Comparaison entre les différents modèles électriques et détermination des paramètres de la caractéristique IV d'un module photovoltaïque. Journal of Renewable Energies, 2010, vol. 13, no 3, p. 379–388-379–388.
[9] CHEN H., JIAO S., WANG M., et al. : Parameters identification of photovoltaic cells and modules using diversification-enriched Harris hawks optimization with chaotic drifts. Journal of Cleaner Production, 2020, vol. 244, p. 118778.
[10] EBRAHIMI S. Mohammadreza S., Esmaeil M M., et al. : Parameters identification of PV solar cells and modules using flexible particle swarm optimization algorithm. Journal of Energy, 2019, vol. 179, p. 358-372.
[11] VILLALVA M G., GAZOLI J R., et RUPPERT F E.: Comprehensive approach to modeling and simulation of photovoltaic arrays. IEEE Transactions on power electronics, 2009, vol. 24, no 5, p. 1198-1208.
[12] VALLÉE T. et YILDIZOĞLU M.: Présentation des algorithmes génétiques et de leurs applications en économie. Revue d'économie politique, 2004, p. 711-745.
[13] BOULAYOUNE A., GUERROUDJ C., SAOU R., et al. : Optimisation par essaim de particule et algorithme génétique d'une machine à inversion de flux. Rev. Roum. Sci. Techn. Électrotechn. et Énerg, 2017, vol. 62, p. 19-24.
[14] KUMAR S., SINGH A., et DHAR A. : Parameter extraction using global particle swarm optimization approach and the influence of polymer processing temperature on the solar cell parameters. AIP Advances, 2017, vol. 7, no 8.
[15] OLIVA D., CUEVAS E. et PAJARES G.: Parameter identification of solar cells using artificial bee colony optimization. Energy, 2014, vol. 72, p. 93-102.
[16] JEAN J., BROWN P R., JAFFE R L., et al. : Pathways for solar photovoltaics. Energy & Environmental Science, 2015, vol. 8, no 4, p. 1200-1219.
[17] SINGH G K.: Solar power generation by PV (photovoltaic) technology: A review. Energy, 2013, vol. 53, p. 1-13.
[18] ELTAWIL M A. et ZHAO Z. : Grid-connected photovoltaic power systems: Technical and potential problems—A review. Renewable and sustainable energy reviews, 2010, vol. 14, no 1, p. 112-129.
[19] CHELLASWAMY C. et RAMESH R. : An optimal parameter extraction and crack identification method for solar photovoltaic modules. ARPN Journal of Engineering and Applied Sciences, 2016, vol. 11, no 24, p. 14468-14481.
[20] DALI A., BOUHARCHOUCHE A., DIAF S.: Parameter identification of photovoltaic cell/module using genetic algorithm (GA) and particle swarm optimization (PSO). In: Proceedings of the 3rd International Conference on Control, Engineering & Information Technology (CEIT), Tlemcen, Algeria, 25-27 May, 2015. IEEE, 2015. p. 1-6.
[21] HARRAG A. , MESSALTI S.: Three, five and seven PV model parameters extraction using PSO.). In: Proceedings of the International Conference on Technologies and Materials for Renewable Energy, Environment and Sustainability, TMREES17, Beirut Lebanon , 21-24 April 2017, Energy procedia, 2017, vol. 119, p. 767-774.
[22] VILLALVA M.G., GAZOLI J.R, et RUPPERT F E.: Modeling and circuit-based simulation of photovoltaic arrays. In : Proceedings of Brazilian Power Electronics Conference , IEEE, 2009. p. 1244-1254.
[23] SERRA R. et OLIVIER J.: Apport de l'optimisation par essaims particulaires pour la détection de modifications structurelles à partir des propriétés dynamiques. In : Proceedings of the 23ème Congrès Français de Mécanique CFM 2017. AFM, Maison de la Mécanique, 39/41 rue Louis Blanc-92400 Courbevoie, 2017.
[24] Gharib A., Benhra J.: Tuning manuel de l'algorithme d'optimisation par essaims de particules appliqué au problème de voyageur de commerce. Xème Conférence Internationale : Conception et Production Intégrées, Dec 2015, Tanger, Maroc. ffhal-01260694
[25] HAMID N F A., RAHIM N A., et SELVARAJ J.: Solar cell parameters extraction using particle swarm optimization algorithm, in: Proceeding of the conference on clean energy and technology (CEAT). IEEE, 2013. p. 461-465.
[26] MOTAHHIR S., EL GHZIZAL A., SEBTI S., et al: Proposal and implementation of a novel perturb and observe algorithm using embedded software. In : : preceding of the 3rd International Renewable and Sustainable Energy Conference (IRSEC). IEEE, 2015. p. 1-5.
[27] CHERMITTI A. , BENCHERIF M. , BECHAR H.: Évaluation des paramètres d'un panneau solaire.in: proceedinf of the 16èmes Journées Internationales de Thermique (JITH 2013) Marrakech (Maroc), du 13 au 15 Novembre, 2013